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Optimization of Process Planning System for Prismatic Parts using ACO

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Abstract—*Process planning having important role in manufacturing industries. A best process plan can give better results in terms of cost or time, sometimes even both. Computer aided process planning helps in integrating Computer aided modeling and computer aided manufacturing. There is a great revolution in the terms of CAPP with generative type systems. Artificial intelligence techniques are helping to solve these combinatorial optimization (CO) problems. Ant colony optimization gives good heuristic information to solve these CO problems. An improved mutated ant colony optimization is proposed and is applied to process planning. The objective function taken in this paper is 'Minimization of Time'. By which total manufacturing time is optimized. The proposed algorithm able to give best optimized sequence of operations and suggests machines and tools to be use in processing a part/component.*

Keywords: *Process Planning, Ant colony algorithm, combinatorial optimization, Precedence relationship matrix.*

1. INTRODUCTION

Computer aided design (CAD) is the use of computer systems to assist in the creation, modification, analysis, or optimization of a design. A system of using computer technology to assist the manufacturing process is Computer aided manufacturing. There is an intermediate stage in between computer aided design and computer aided manufacturing, Process planning plays an important role for making a product. The process planning task involves many activities, like selection of machining operations, cutting tools, and cutting parameters, ordering of operations, and calculation of setup and fixtures, by considering all the available resources, it plans for reducing lead time, cost of the product. Manual process planning is very difficult for prismatic parts with complex structure. To increase efficiency of manufacturing there is a need for CAPP, It will consider all the constraints and gives a best process plan. These types of combinatorial optimization problems can be solved by using artificial intelligence techniques.

ACO ant colony optimization is a swarm Intelligence technique, inspired from real ant's behavior. Swarm intelligence (SI) is a type of artificial intelligence based on the collective behavior of decentralized, self-organized systems. Ant leaves a chemical called pheromone on the way back from food source to their colony, these pheromone trails will help other ants to find the food source in shortest path.

This is an approach to solve the combinatorial optimization problems using heuristic search technique. In this paper an improved ant colony optimization with mutation, approach is used to achieve the global lowest manufacturing time by considering all the precedence constraints.

1.1 Ant Colony Optimization

In the early 1990s, ant colony optimization (ACO) was introduced by M. Dorigo and colleagues as a novel nature-inspired metaheuristic for the solution of hard combinatorial optimization (CO) problems. ACO belongs to the class of metaheuristics, which are approximate algorithms used to obtain good enough solutions to hard CO problems in a reasonable amount of computation time. Inspired from the behaviour of real ants. When searching for food ants initially explore the area surrounding to their colony randomly. When they find the food source they analyze the quality and quantity of food and takes some of it back to their colonies. While going back they deposit chemical known as pheromone material. When a next ant goes for finding the food they take the same path by sensing the pheromone trail. After sometime as the all ants follow the same path to find the food source the path is fully deposited with pheromone trails. The ants find the food source from the pheromone trails. (Due to behaviour the of decentralized and self organized system, by apply)

Double bridge problem can explain the behaviour of ants. In this fig(a) shows that distance from R to S, R to Q, P to S, P to Q. Here ants are moving from "T" TO "U" and coming back. when they come to the point "R" randomly half of the ants chooses the path towards "Q" and half of the ants chooses "S" at time T=0 shown in fig(b). Ants finally reach the point "T". When ants moves towards "T" ants deposits pheromone material on their paths. As pheromone material evaporates in a little time, so the pheromone trails on the path P-Q-R will evaporates faster than the path P-S-R. So the ants from T attracts the path P-S-R than P-Q-R at time T=1 shown in fig (c).

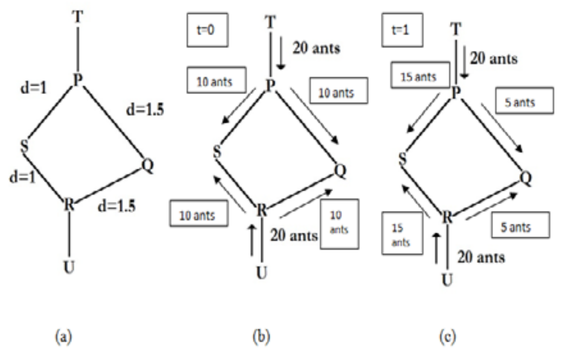


Fig. 1: Double bridge example

Even though some ants take the path D-H-B when the time being the pheromone trails on the path P-Q-R will evaporate in very less time due to ants travelling in this path are less. On the path P-S-R more pheromone trails attracts more ants towards this path. So finally all the ants will choose the path U-R-S-P-T, which is shortest path.

This technique is first implemented successfully on travel salesmen problem (TSP). Later on it is implemented on other combinatorial optimization problems.

2. FORMATTING YOUR PAPER

In the last few decades CAPP have improved by using Artificial Intelligence techniques. Many optimization approaches have been developed and applied on process planning to solve the combinatorial problems. By using genetic algorithm (GA), artificial neural networks (ANN), tabu search technique (TS), artificial immune system (AIS), simulated annealing (SA), particle swarm optimization (PSO), and ant colony optimization (ACO). Nataly Medina-Rodriguez. [3] Is proposed a parallel ACO algorithm to find best sequence for hole cutting that shortens the cutting tool travel path. TSP (travelling salesmen problem) technique is used to solve the problem and optimized the tool travel path by 30%. P.S srinivas, C.S.P Rao. [5] applied the ACO algorithm to solve the problem of generating optimal process plan for a component. The approach models process plan considering the machine, tool and tool approach directions for each operation. Precedence relationships among all the operations required for a given part are used as the constraints for the solution space. The optimal process plan is found based on the minimum total cost criteria. JinFeng Wang.[4] An improved ACO approach is developed to solve the process planning optimization problem for prismatic parts. The approach is characterised in two aspects, (i) A weighted graph is used to represent process planning problems. The graph includes nodes set, directed arcs set and undirected arcs set, which denotes operation, precedence constraints between the operation and possible visited path connecting the nodes respectively. (ii) a pheromone updating strategy proposed in this proposed ACO is incorporated in the standard ACO. This includes Global update rule and Local update rule. A simple method by controlling the repeated number of the same process plan is determined to avoid the local convergence. C.W. Leung. [8] An ant colony optimization algorithm is developed for the integrated process planning and scheduling problems. Motivated from the advantages of distributive computation and scalability of the MAS behaviours, the ACO algorithm is implemented on the established multi-agent platform. To affect the ACO approach, a graph-based solution method is proposed to represent sets of alternative processes and machines. Nan Zhao. [7] Proposed a MACO algorithm, which can enlarge searching range and avoid local minima by introducing the mutation mechanism to the ACO algorithm. So, the performance MACO is superior to that ACO algorithm with almost the same computational complexity.

3. PROPOSED METHODOLOGY

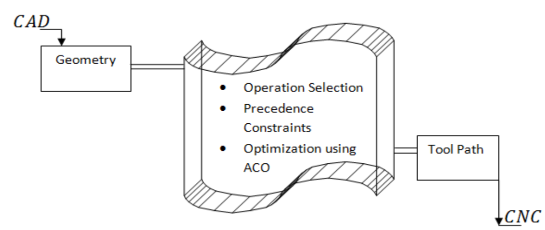


Fig. 2: Proposed Methodology

The work process to develop an integrate CAD/CAM system by generating an optimum tool path. The block diagram in fig shows the step by step procedure of proposed methodology.CAD involves in designing a part. Process planning involves in identifying the operations required, precedence constraints, assigning machines and tools in a proper sequence to reduce the lead/process time or any other factor. There will be number of possible solutions for a component, in that only one solution gives you a best output. It is difficult to find the solution for a component and even more difficult to find for prismatic components with difficult structures. By using artificial intelligence optimization process planning can be done, this type of process planning is known as Generative type. Implementing ACO algorithm to find best possible sequence. Hear each best sequence, each and every operation are mutated, for getting best optimized sequence. With this best sequence tool path is generated and manufacturing is done by using CAM.

4. DEVELOPMENT OF PROCESS PLANNING SYSTEM

Development of process planning which involves both design and manufacturing attributes. There is a need in developing

Process planning system for the betterment of manufacturing. In the following chapters it was explained the involvement of Modelling and Manufacturing attributes.

4.1 Modelling

We get all the design details for the CAD model, by which we define all the factors which helps for process planning. Constraints for manufacturing are defined by using CAD model. From the topology of the component we can define the type of manufacturing need to implement. Defining features of the component plays a vital role in selecting the machines and tools. Setup changes and tool approach directions are defined by using CAD model. These factors are inputs for process planning.

4.2 Optimization of Process Planning using ACO

If a component/part having 'm' number of features, each and every feature is a node and arcs are used to join the two nodes. Initially 'm' numbers of artificial ants needs to be send in the search space in random ways and need to cover all the nodes. We get m factorial possible ways, segregating these possible ways by using precedence constraints. Finally we get 'x' number of possibilities which obeys all constraints. Solving this combinatorial optimization problem needs a good heuristic search technique. Heuristic value on the node and pheromone trails on the arcs helps in selecting possibility destination node or feature.

Heuristic information is given by the following equation

$$\eta_{x,y} = \frac{G}{PT} \quad (1)$$

$\eta_{x,y}$ Gives the heuristic value of destination of y from source x. G is the positive constant and it can be set by trial and error. PT is the processing time of the selected node.

$$\text{PT} = MPT_i + TPT_i \quad (2)$$

MPT_i is the machine processing time for the i^{th} operation and TPT_i is the tool processing time for i^{th} operation.

The nodes having low processing time will have more heuristic value. If R is an ant, more heuristic value on the nodes has more attraction for R^{th} ant.

For an ant, to move from one node to other is given by selection probability P_{xy}^{R}. This can be constructed from the heuristic information on the node y and pheromone value on the arcs connected by x,y.

$$P_{xy}^{R} = \begin{cases} \frac{[\tau_{xy}^{R}]^{\alpha} \, [\eta_{xy}]^{\beta}}{\sum_{w \epsilon s_k} [\tau_{xz}^{R}]^{\alpha} \, [\eta_{xy}]^{\beta}} & \upsilon \epsilon s_k \\ 0 & \upsilon \notin s_k \end{cases} \quad (3)$$

Where υ is the destination node, s_k is the set of nodes allowed by the ant R, $\alpha \; and \; \beta$ denotes the weighting parameters controlling the relative importance of pheromone amount and the heuristic information, respectively.

I. Pheromone update

To increase the speed of the algorithm a simple pheromone update strategy is proposed in the standard ACO, which includes two pheromone update rules, local update rule for the elite process planning is incorporated into the global update rule. Three types of process planning solutions are specified at different stages as to incorporate the pheromone updating strategy. Best solution of current iteration Li, best solution from the last restart Lk and best solution from the starting of the algorithm Lb. Lavg is the average total processing time since the last restart and calculated as:

$$L_{avg} = \frac{\sum_{i=1}^{R_{ite}} L_i}{R_{ite}} \quad (4)$$

When an ant 'a' starts its tour it can start from any node. It ends the tour by covering all the nodes. Initially set all the pheromone value ($\tau_{x,y}$) equal to constant value i.e., e = 0.1 for every pair of operation. $\tau_{x,y}$ from source x to destination y Gives the value of pheromone trail on the arc. The objective function for each sequence is calculated. Now update the pheromone value differentially. To control the unlimited accumulation of pheromone deposited, pheromone evaporation should be done after every iteration. The pheromone amount can be given as:

$$\tau_{xy}^{R} = (1-\rho) * \tau_{xy}^{R} + \Delta\tau_{xy}^{R} \quad (5)$$

Where ρ is the pheromone evaporation coefficient from source x to destination y and $\Delta\tau_{xy}^{R}$ is the quantity of the pheromone update on the arc (x,y) generated by ant R after each iteration.

$$\Delta\tau_{x,y}^{R} = \begin{cases} \frac{w}{L_k} \; if \; L_k \leq L_{avg} \; ant \; R \; passes \; the \; arc(x,y) \\ 0 \; otherwise \end{cases} \quad (6)$$

Where W is a positive constant. L_k is the total processing time by the ant R.

To accelerate convergence of the algorithm to optimal process plan, Local update is introduced. So that the elite process plan solutions are used to update the pheromone on the arcs again. This can be given as:

$$\Delta\tau_{xy}^{r} = \begin{cases} \frac{w}{L_r} \; if \; (L_r \leq L_k) \; or \; (L_r \leq L_b) \\ 0 \; otherwise, \end{cases} \quad (7)$$

Where w is the positive constant and Lr is the total processing time by the ant R.

II. Process Planning Criteria

Lots of process planning criteria has been proposed in the past literatures. The criteria of minimum production cost are generally used. In this paper proposed minimum production time is used. The production time evaluation process planning comprise five factors: machining process time (MT), machine change time (MCT), tool change time (TCT) and setup change time (SCT). The calculation procedures of these time factors are described in detail below:

(i) Total machine processing time (TMPT):

$$\mathrm{TMT}=\sum_{i=1}^{n} \mathrm{MPT}_i \qquad (8)$$

Where n is the total number of operations and MPT_i is the machine time of the ith machine for an operation, a constant for a specific machine;

(ii) Total setup time (TST):

$$\mathrm{TST}=\mathrm{SCT} * \mathrm{NS} \qquad (9)$$

Where SCT is the setup time and NS is the number of setups, which can be calculated by

(iii) Total machine change time (TMCT):

$$\mathrm{TMCT} = \mathrm{MCT} * \mathrm{NMC} \qquad (10)$$

Where MCT is machine change time and NMC is number of machine changes

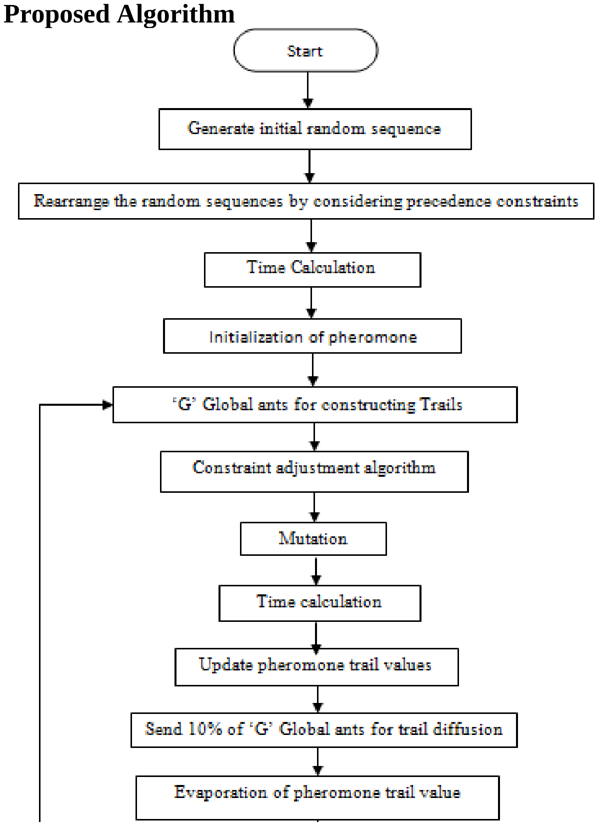
(iv) Total tool change time (TTCT):

$$\mathrm{TTCT} = \mathrm{TCT} * \mathrm{NTC} \qquad (11)$$

Where TCT is tool change time and NTC is number of tool changes.

(i) When there is no machine changing then the total machining change time will be zero.
(ii) When there is machine change, the setup time will be zero.

III. Proposed Algorithm



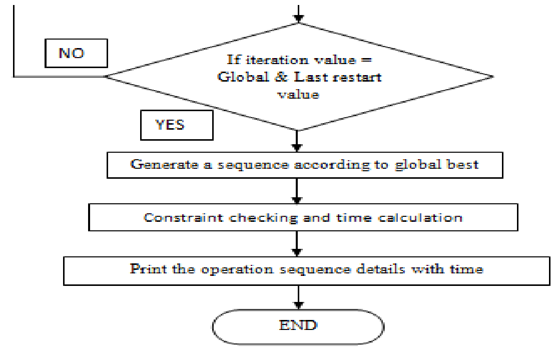


Fig. 3: Flow chart of ACO algorithm for process planning

In this proposed algorithm pheromone update is done twice in global level and local level, this differs from other algorithms. And this accelerates the best process plan. After all iterations completed the best operation sequence for the objective function is printed.

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5. IMPLEMENTATION OF PROPOSED METHOD

The proposed work has been implemented by taking an example of a prismatic part having 13 features and 18 operations. The example part is modeled by using CATIA. This model is having different features and complex structure. The details of this part are given below.

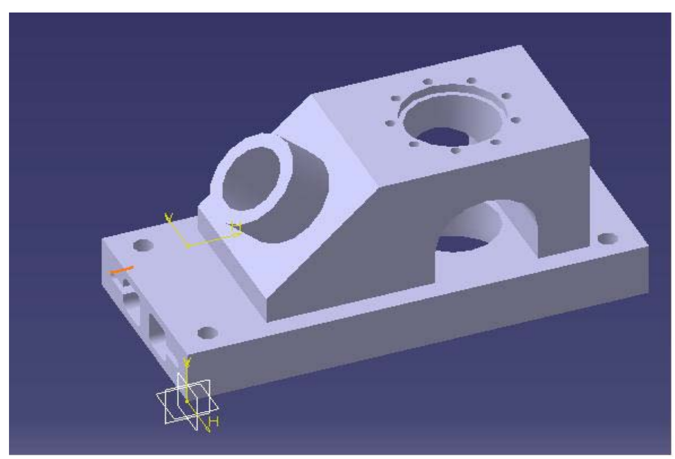

Fig. 4: Example part

5.1 Precedence Constraints among Operations

Precedence constraints are derived from the details of example model and it explains the relation between the features. The precedence constraints need to be considered for a better manufacturing practice. The following table gives constraints between the operations to be performed.

Table 1: Precedence Constraints Matrix

	Prior to																	
List Of Operations	OP1	OP2	OP3	OP4	OP5	Op6	Op7	OP8	OP9	OP10	OP11	OP12	0P13	OP14	OP15	OP16	OP17	OP18
OP1																		
OP2	✓																	
OP3	✓																	
OP4	✓				✓													
OP5	✓																	
OP6	✓																	
OP7	✓					✓												
OP8	✓	✓				✓	✓											
OP9	✓	✓				✓	✓	✓										
OP10	✓																	
OP11	✓									✓								
OP12	✓	✓																
OP13	✓	✓										✓						
OP14	✓				✓													
OP15	✓				✓													
OP16	✓				✓													
OP17	✓				✓													
OP18	✓																	

5.1 Selection of Machines and Tools

From the geometric details of the example model below mentioned machines and tools are considered among the available machines and tools, and feature description are also included in the below table.

Table 2: Details of Machine description

Machines	Indications
Drilling Press	M1
Three axis vertical milling machine	M2
CNC 3-axis vertical milling machine	M3

Table 3: Details of Tool description

Tool	Indication
Drill-1	T1
Drill-2	T2
Drill-3	T3
Drill-4	T4
Tapping tool	T5
Mill-1	T6
Mill-2	T7
Mill-3	T8
Ream	T9
Boring	T10

Table 4: Index of M/C change, Tool change, Machining time

Tool Changing Time Index in Minutes	
Drilling Machine	0.30
Vertical Milling Machine	2
CNC 3-axis Vertical Milling Machine	0.50
Machine Changing Time Index in Minutes	
Drilling Machine	5.50
Vertical Milling Machine	12
CNC 3-axis Vertical Milling Machine	15
Machining Time Index for stainless steel	
MRR in CNC- 3axis	3.18 in3/min
MRR in conventional milling	0.91 in3/min
Drilling - Feed rate	6.0 in/min

Table 5: Selection of Machines, Tools

Features	Feature Description	Operations	Machines	Tools
F1	Planar surface	Milling(OP1)	M2,M3	T6,T7,T8
F2	Planar surface	Milling(OP2)	M2,M3	T6,T7,T8
F3	Two replicated pockets	Milling(OP3)	M2,M3	T6,T7,T8
F4	Four replicated holes	Drilling(OP4)	M1,M2,M3	T1
F5	A step	Milling(OP5)	M2,M3	T6,T7
F6	A boss	Milling(OP6) Drilling(OP7)	M2,M3 M1,M2,M3	T7,T8 T2,T3,T4
F7	A compound hole	Reaming(OP8) Boring (OP9)	M1,M2,M3 M2,M3	T9 T10
F8	A compound pocket	Milling(OP10) Milling (OP11)	M1,M2,M3 M2,M3	T9 T10
F9	Ten replicated holes	Drilling(OP12) Tapping(OP13)	M1,M2,M3 M1,M2,M3	T1 T5
F10	A pocket	Milling(OP14)	M2,M3	T7,T8
F11	A compound hole	Milling(OP15) Boring(OP16)	M2,M3 M2,M3	T6,T7 T6,T7,T8
F12	A pocket	Milling(OP17)	M2,M3	T6,T7,T8
F13	A hole	Boring(OP18)	M2,M3	T10

5.3 Optimal Process plan

When applying ACO in process planning, need to be consider parameters $\alpha, \beta, G, \rho, w$. For this problem taken the values as $\alpha \in (0.1, 1, 5)$, $\beta \in (0.1, 1, 5)$, G=50, $\rho = 0.75$, w=2000. The no.of ants to be initialized will be an important factor, when less no.of ants are considered the optimization rate will become very slow. If no.of ants are considered then the computing time will be long.

The optimal process plan for the example component is below:

Process plan: 1-5-2-15-16-6-7-8-9-4-12-13-3-10-11-17-18

Machine no: M2-M3-M3-M3-M3-M3-M3-M3-M3-M1-M1-M1-M3-M3-M3-M3-M3

Process time: 3.5, 6.20, 2.04, 0.52, 1.7, 2.53, 0.12, 0.07, 4.52, 0.57, 0.10, 11.11, 13.30, 0.54, 0.54, 0.52

Tool no: T8- T7 - T7-T10-T8-T6-T3-T9-T10 -T1-T1-T5-T7-T7-T8-T8-T10

No.of machine changes: 3

No.of tool changes: 9

No.of setup changes: 4

Total manufacturing time: 147.68 min

6. CONCLUSION

In this paper we implemented ant colony optimization on process planning. ACO algorithm is a good heuristic search technique to solve combinatorial optimization problems. We included a pheromone updated strategy in this algorithm i.e., global update rule and local update rule. In this paper we applied on a prismatic part. The approach model process planning considered the machines and tools for each operation. Required precedence constraints are used as constraints for solution space. Here we got optimal process plan is based on the minimum total manufacturing time. When compared the same results with the results from genetic algorithm there is a large change in the value.

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